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Multiobjective Optimization of the Production Process for Ground Granulated Blast Furnace Slags

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Abstract The production process of ground granulated blast furnace slag (GGBS) aims to produce products of the best grade and the highest yields. However, grade and yields are two competing objectives which can not be optimized at the same time by one single solution. Meanwhile, the production process is a multivariable strong-coupling complicated nonlinear system. It is hard to establish the accurate mechanism model of this system. Considering above problems, we formulate the GGBS production process as an multiobjective optimization problem, introduce a least square support vector machine (LS-SVM) method based on particle swarm optimization to build the data-based system model and solve the corresponding multiobjective optimization problem by several multiobjective optimization evolutionary algorithms (MOEAs). Simulation example is presented to illustrate the performance of the presented multiobjective optimization scheme in GGBS production process.

Keywords Ground granulated blast furnace slag · multiobjective optimization · MOEA · PSO based LS-SVM

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1 Introduction

As a by-product of iron and steel-making, about 200 million tons of granulated blast furnace slag was produced in China in 2015. It has been a heavy environmental and financial burden for both iron and steel enterprises and the government. However, when dried and ground into particles thinner than 400 m^2/kg, it becomes a new kind of product called ground granulated blast furnace slag or slag cement. As a kind of environment-friendly material, GGBS can be mixed into cement to increase its strength and durability, improve its resistance to chloride penetration, and reduce cost (Chithra and Nazeer, 2012; Oner and Akyuz, 2007). Due to its excellent characteristics, GGBS has been widely used in high-rise buildings, hydraulic engineering, transportation and marine projects such as dams and shore protection construction (O'Connell et al, 2012). In recent years, the requirement for high-quality GGBS has risen significantly. However, the reality is that without optimal solution and system model as guidance, parameters are always tuned based on the experience of workers so that the grade and yields are always far away from the optimal solution and vary in a relatively wide permissible range. In the practical production process, it is still a challenging problem to produce high-quality GGBS efficiently.

This challenge comes from two aspects, on the one hand, grade and yields are two competing objectives in the GGBS production process caused by the vertical mill operation mechanism. When higher quality product is required, the efficiency of slag powder selection must be reduced, leading to lower yields and vice versa. On the other hand, vertical mill grinding is a multivariable, strong coupling, nonlinear process with complicated physical and chemical reactions. Hence, the accurate mechanism model of GGBS production process is hard to be established. Chen (2008) analyzed the fluid mechanics effect of particles in vertical mill, and discussed the relationships between particles' fineness and each variables. Although Chen's work has an important effect on revealing the grinding mechanism in vertical mill, it dose not establish the whole mathematical model as the GGBS production is a comprehensive system with multiple variables.

Instead of relying on the information of system model, data-driven control can achieve the modernization and control between output and measurable process variables, using only the online and offline data. For the cement production process of vertical mill grinding system, data-driven control is being widely studied, trying to accurately identify the complex grinding system. For cement raw meal grinding system, Cai et al (2013) achieved indirect measurement by establishing a soft sensor model of the material thickness based on the method of least squares support vector machine (LS-SVM). Lin and Qian (2014) built a production index prediction model of vertical mill raw material grinding using a wavelet neural network, and obtained the optimal set points. However, to the best of our knowledge, there are few papers studying data-based models of the GGBS production process. Wang et al (2016) discussed the establishment of the data-based model by using a recurrent neural network, and realized the optimal tracking control for GGBS quality and grinding pressure difference. However, it did not take yields into consideration and the set points were predefined based on experience rather than optimal values.

Grade and yields are the two competing objectives which need to be taken into consideration in the GGBS production process. These multiobjective optimization problems (MOPs) are different since there are a set of alternative optimal solutions, rather than a single one. Due to the ability to obtain the Pareto set in a single run, evolutionary algorithms (EAs) have been introduced to solve MOPs. Many popular algorithms emerge, such as the nondominated sorting genetic algorithm II (NSGA-II) (Deb et al, 2002), strength Pareto EA 2 (SPEA2) (Zitzler et al, 2002), and decomposition-based multiobjective EA (MOEA/D) (Zhang and Li, 2007).

In this paper, we consider grade and yields as the optimal objectives for the GGBS production process. Meanwhile, to maintain a stable operation, every control variable and grinding pressure difference must be kept in permissible ranges. To establish the accurate data-based models of objectives and constraint, particle swarm optimization (PSO) is introduced to optimize the parameters in the LS-SVM algorithm. Further, based on the above models and constraints, the MOP of the GGBS production process is constructed.. Finally, different multi-objective algorithms are explored to obtain the ideal Pareto set.

The rest of the paper is organized as follows. Section 2 introduces the multiobjective optimization (MO) problem of the GGBS production process. MO strategies are presented in Section 3. In Section 4, an experiment is conducted to show the result of the proposed optimization strategy and Section 5 concludes this paper.

2 MO problem of the GGBS production process

In this section, the general description of MOPs is given first, then the GGBS production process and corresponding main objectives are briefly introduced, and finally the MOP of the GGBS production process is given.

2.1 Description of MOPs

In practical engineering, there are many design and decision problems with multiple competing objectives. To find the optimal solutions under multiple objectives and constraints, the problem must be solved as an MOP (Jiang and Yang, 2016).

Usually, an MOP can be defined to maximize (or minimize) different objective functions under some constraints. An MOP can be formulated as

$$\begin{cases} \max/\min \quad [f_1(\boldsymbol{x}), \cdots, f_i(\boldsymbol{x}), \cdots, f_p(\boldsymbol{x})] \\ \text{s.t.} \\ g_j(\boldsymbol{x}) \le 0, j = 1, 2, \cdots, J \\ h_k(\boldsymbol{x}) = 0, k = 1, 2, \cdots, K \end{cases} \tag{1}$$

where $\boldsymbol{x} = (x_1, x_2, \cdots, x_m)$ denotes the state vector with m elements, $f_i(\boldsymbol{x})$, $i = 1, 2, \cdots, p$ are the objective functions, $g_j(\boldsymbol{x}) \le 0$, $j = 1, 2, \cdots, J$ and $h_k(\boldsymbol{x}) = 0$, $k = 1, 2, \cdots, K$ are system constraints.

In most cases, there is no single optimal solution which is the best for all objectives. For example, one solution is best for one objective, but may be worst in the sense of other objective since objectives are always competing. Hence, there are a set of optimal solutions that no other solutions are better than them in the sense of all objectives. They are known as Pareto-optimal solutions. The goal of solving an MOP is to find as many Pareto-optimal solutions as possible (Coello et al, 2002).

2.2 Production process of GGBS

A GGBS grinding system mainly consists of belt weigher, vertical mill, material conveyer belt, dust collector, and fan equipment. After preprocess, raw material–blast furnace slag–will be weighed by the belt weigher and then transported into the vertical mill. Under the centrifugal force caused by rotation of grinding disc, material moves to the edge of the grinding disc, and falls into the bottom of grinding roller, where it is ground by rotating roller under the hydraulic pressure and keeps moving towards disc edge. After grinding, material moves across material barrier into wind ring, where it is dried and taken up to the top of mill by hot high-speed wind for further separation. Qualified powder will be extracted outside the mill as GGBS product, and coarse particles drop down to the disc for further grinding. The monitor screen and workflow of the GGBS production process are shown in Fig. 1 and Fig. 2 respectively.

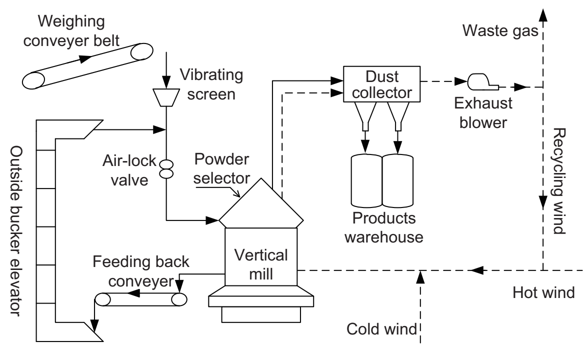

Fig. 2 GGBS grinding workflow

2.3 Process index of the GGBS production process

The main target of the GGBS production process is to get the optimal solution for both grade and yields. At the same time, grinding pressure difference must be limited to guarantee a stable operation.

2.3.1 Product grade

Specific surface area (SSA) – indicator of the fineness of product particles – is the index for product's grade. When slag is ground to be finer than 400 m^2/kg, it can be mixed into cement to improve the mechanical property of concrete. Super fine GGBS is slag powder finer than 500 m^2/kg, which becomes more active and shows higher mechanical property than the normal GGBS.

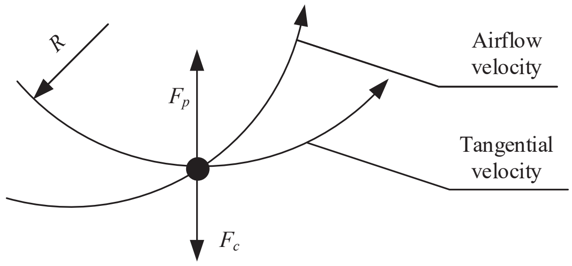

Fig. 3 Force analysis of GGBS particles

In the GGBS production process, many factors have impacts on SSA. Feeding materials' property, speed and moisture content are important parameters affecting S-SA. Hot air into mill not only dries materials in mill but also takes particles up to the selector for selection. Hot air's volume, speed and temperatures at inlet and outlet all have important effect on SSA. On the premise of constant air speed, larger air volume will increase yields of selector and decrease slag powder's fineness and vice versa. Air volume is controlled by tuning the opening of the circulating air damper. The rotational speed of the selector is the most direct parameter for product's grade and yields. As shown in Fig. 3, there are two main forces acting on particles in the grading force field, the centrifugal force F_c decided by the rotational speed of the selector, and the pull force F_p caused by air speed. These two forces decide what kind of fineness can be selected as qualified product. When the rotational speed is faster, the centrifugal force gets larger and only finer particles can be selected, less qualified particles means lower yields at the same time. As the air volume and speed out mill do not vary too much, adjustment of the rotational speed of the selector is the main method to control the grade of GGBS.

2.3.2 Product yield

Besides product grade, yields of GGBS is another important target in the production process. In above analysis about production grade, it is obviously that the feeding material, air volume in mill and rotational speed of selector also have effect on product yields at the same

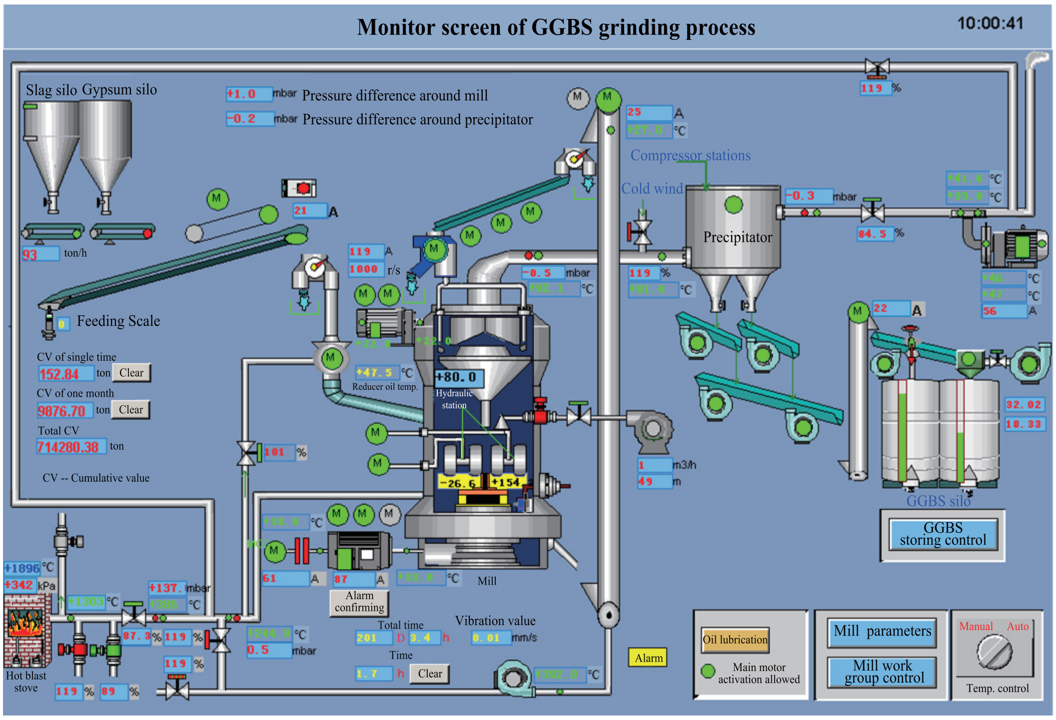

Fig. 1 Monitor screen of GGBS production process

time. In practical production process, grade and yields are two coupling and competing objectives.

2.3.3 Grinding pressure difference

Grinding pressure difference (GPD) denotes the error between the pressure under selector in the mill and the pressure at the inlet of hot wind. In normal circumstance, GPD is stable, which means that it achieves a dynamic balance between the amount of material into the mill and the amount of material out of the mill. Decreased GPD indicates that materials into mill is less than that out of mill, thickness of material layer will continue decreasing until the mill vibrates and shuts down. On the other hand, increased GPD indicates material into mill is more than that out of mill. In severe case, it will lead to saturated grinding and mill vibration. Generally, GPD can be adjusted by tuning the slag feed rate, and it is kept within 25–35 mbar to ensure the stability of the GGBS production process.

2.4 GGBS production process as an MOP

Based on the above analysis, grade and yields of the GGBS product are the two most important indexes for the GGBS production process, and these two targets are both decided by some identical variables which are interrelated and interactive. If we demand higher grade, the efficiency of powder selector will be reduced and GPD will be increased. To avoid mill vibration caused by high GPD, the slag feed rate must be decreased, leading to the decline of product yields. If we demand high yields, high efficiency is needed to balance the GPD, resulting in worse product grade.

Table 1 Daily reports of LUXIN mill line 3

No.	Time Hrs	Average yields MT/Hr	Average grade m^2/kg
1	24	82.8479	443.9333
2	9.5	87.5415	429.5254
3	24	76.8333	436.2417
4	24	80.7342	429.4106
5	24	86.3438	435.7083
6	24	86.2838	434.2583
⋮	⋮	⋮	⋮
59	23.5	84.8507	421.0917
60	24	84.8373	423.4758

Through analysing the daily reports of LUXIN mill line 3 from 12 January, 2013 to 31 March, 2013, we obtain 60 groups of production data describing the average yields and average grade of the product during the operation hours in each day as shown in Table 1. After unreasonable data deletion and data normalization, we get 34 groups of data depicting the grade-yields relationship shown as Fig. 4. The average grade and yields of GGBS in practical production process are negatively related and the correlation coefficient is calculated to be −0.7305. Although the rough curves can not illustrate the accurate relationship between grade and yields, they are in accordance with the mechanical analysis in Section 2.3 that grade and yields are competing and can not be optimal at the same time.

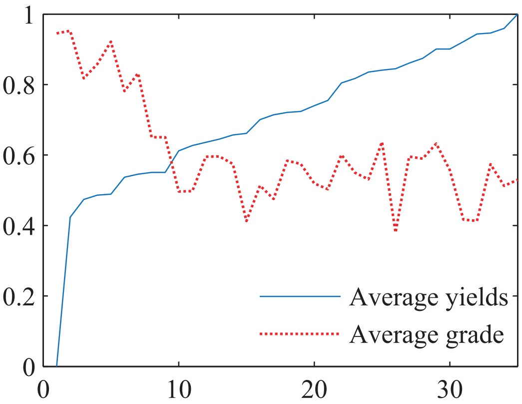

Fig. 4 Relationship between grade and yields

For the production process of GGBS, the main optimization goals are to maximize grade and yields of GGBS product and to let the GPD vary in a given range, corresponding variables are the slag feed rate, separator rotor speed, wind temperature at mill inlet, circulating air damper opening and roller pressure. Because the system is hard to be modeled mechanically as it is multivariable, strong coupling, complicated and nonlinear, we try to establish the data-based system model as

$$(y_1, y_2, y_3) = F(x_1, x_2, x_3, x_4, x_5, x_6) \tag{2}$$

where, y_1 is the grade, y_2 is the yields of GGBS, y_3 is the GPD, x_1 is the slag feed rate, x_2 is the roller pressure, x_3 is the separator rotor speed, x_4 is the temperature at mill inlet, x_5 is the temperature at mill outlet, and x_6 is the opening of the circulating air damper.

As these two objectives in the GGBS production process are negatively related and competing with each other, there is no one solution which is best for both objectives at the same time. Hence, the GGBS production process is a typical MOP which can be formulated as

$$\begin{cases} \max & y_1 \\ \max & y_2 \end{cases}$$
$$s.t. \begin{cases} x_i^l \le x_i \le x_i^u \\ y_1^l \le y_1 \\ y_3^l \le y_3 \le y_3^u \\ (y_1, y_2, y_3) = F(x_1, \cdots, x_i, \cdots, x_6) \end{cases} \tag{3}$$

Table 2 Permitted ranges of variables and GPD

Variables	Maximum	Minimum	Units
x_1	115	75	10^3kg/Hr
x_2	130	100	bar
x_3	1210	860	r/min
x_4	300	190	°C
x_5	125	75	°C
x_6	95	30	%
y_3	30	20	10^3kg

where $i = 1, 2, \cdots, 6$, x_i^l and x_i^u are the lower and upper bounds of x_i, y_1^l and y_1^u are the lower and upper bounds of y_1, y_3^l and y_3^u are the lower and upper bounds of y_3. The first constraint guarantees every control variable in given ranges, the second constraints the SSA to guarantee the production qualified, and the third constrains the GPD to ensure the production process safe and stable. According to the physical constraints of every actuator and the experience of expert engineer, the permitted ranges of variables and GPD are listed in Table 2.

3 Multiobjective optimization strategy of the GGBS production process

As mentioned above, the production process of GGBS is an MOP. Meanwhile, the process is hard to be modeled because it is a multivariable strong coupling complicated nonlinear system. To address these problems, we apply the proposed multi-objective strategy to optimize the system based on an established data-based model.

3.1 The multiobjective GGBS process optimization model

In this section, we will preprocess raw data, analyze control targets, variables and constraint conditions, finally establish the data-driven model between control targets and variables based on the LS-SVM method (Suykens and Vandewalle, 1999).

3.1.1 Data preprocessing

A neural network (NN) is a model identification strategy driven by process data, so the effect of NN identification relies on the quantity and quality of samples. However, practical production process is usually influenced by many factors, leading to inevitably inaccurate sample data. Therefore, quality improvement of samples plays a critical role to establish an accurate model.

Table 3 Production data of LUXIN mill line 3

No.	Slag counter 10^3 kg/Hr	Poller pressure bar	Separator rotor speed r/min	Temp. at mill inlet °C	Temp. at mill outlet °C	Opening of air damper %	SSA m^2/kg	Yields mbar	GPD 10^3kg
1	100.46	120	1069.07	215.00	100.00	67.27	423.20	29.83	92.97
2	105.05	125	1029.64	240.90	100.10	59.81	426.40	27.43	95.75
3	103.29	126	999.91	252.80	111.29	59.58	434.20	26.16	96.24
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
523	108.19	126	1080.12	260.40	107.77	59.38	423.20	29.05	99.77
524	96.06	105	1050.03	263.70	114.33	61.08	440.10	25.93	89.36
525	95.19	118	1129.97	244.00	105.88	54.89	430.30	26.56	89.33

In this paper, we collected 525 samples in LUXIN the GGBS production process from 12 January, 2013 to 28 February, 2013 as shown in Table 3. The sample set is denoted as $\{\boldsymbol{x}^j, \boldsymbol{y}^j\}_{j=1}^M$, where M is number of samples, $\boldsymbol{x}^j \in R^m$ and $\boldsymbol{y}^j \in R^n$. Denote $\boldsymbol{z}^j = \left(\boldsymbol{x}^j; \boldsymbol{y}^j\right) \in R^{m+n}$. To reduce the gross error and get high-quality samples, raw data is preprocessed in the following procedure

1. Delete data group $\boldsymbol{z}^j$ which contains 0 or empty element. $M = \text{width}\,\{\boldsymbol{z}\}$.
2. According to Grubbs' criterion (Grubbs, 1950), delete data group $\boldsymbol{z}^j$ if any of the following equation holds for $i = 1, \cdots, (m+n)$,

$$|z_i^j - \bar{z}_i| \geq 3s_i \tag{4}$$

   where $\bar{\boldsymbol{z}} \in R^{m+n}$ is the mean value vector and $\boldsymbol{s} \in R^{m+n}$ is the standard deviation defined as $s_i = \{\sum_{j=1}^M (z_i^j - \bar{z}_i)^2/(M-1)\}^2$. $M = \text{width}\,\{\boldsymbol{z}\}$.
3. To eliminate the random noise of samples, the following 7 points moving average smooth method is adopted

$$\boldsymbol{z}^k = \frac{1}{7}\sum_{r=-3}^{3} \boldsymbol{z}^{k+r} \quad k = 4, 5, \cdots, M-3 \tag{5}$$

4. Data normalization.

3.1.2 PSO based LS-SVM model

The LS-SVM has been tested as an effective data-based modeling method which is suitable for many online applications (Shrivastava et al, 2015; Lu et al, 2016). For any nonlinear system, this method has proved its uniform approximation ability, and shows attractive characters such as only solving linear equations, simple algorithm and less computation.

To establish the data-based models between output and variables shown in Eq. (2) and Fig. 5, we adopt the following LS-SVM algorithm.

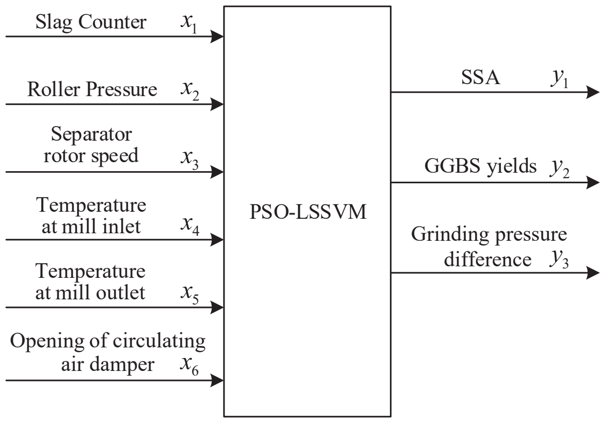

Fig. 5 PSO based LS-SVM model of the GGBS production process

For a given sample set $\{\boldsymbol{x}^j, \boldsymbol{y}^j\}_{j=1}^M$, three data-based models in regard with grade, yields and GPD are expected to be established where $\boldsymbol{x}^j \in R^m$ is the input data and $y_i^j \in R$, $i = 1, \cdots, n$ is the output data respectively.

To model the unknown system precisely, the following equation should be optimized

$$\begin{aligned} &\min_{\boldsymbol{\omega}, b, \boldsymbol{\xi}} \quad J(\boldsymbol{\omega}, \boldsymbol{\xi}) = \frac{1}{2}||\boldsymbol{\omega}||^2 + \frac{1}{2}\gamma \sum_{j=1}^{M} \xi_j^2 \\ &\text{s.t.} \quad y_i^j = \boldsymbol{\omega}^T \varphi(\boldsymbol{x}^j) + b + \xi_j, \quad j = 1, \cdots, M \end{aligned} \tag{6}$$

where the nonlinear function $\varphi : R^m \to R^N$ maps the input to a higher dimension space, $\boldsymbol{\omega} \in R^N$, $b \in R$ denotes the bias term, ξ_j is slack variable and γ is a positive real constant denoted as a tuning parameter in LS-SVM.

Predicted output by LS-SVM can be obtained as

$$\hat{y}_i(x) = \sum_{j=1}^{M} \alpha_j K(\boldsymbol{x}, \boldsymbol{x}^j) + b \tag{7}$$

where α_j and b are solved by a system of linear equations (Suykens and Vandewalle, 1999). In this paper, we adopt the radial basis function (RBF) as the kernel function,

$$K(\boldsymbol{x}, \boldsymbol{x}^j) = \exp(||\boldsymbol{x} - \boldsymbol{x}^j||^2/\sigma^2) \tag{8}$$

where σ is the width of RBF.

It should be noted that parameter σ in the kernel function and tuning parameter γ are critical for the performance of SVM modeling. Compared with EAs, P-SO has the advantages of less parameters, simpler algorithm and faster optimizing speed. In PSO algorithms, there is no evolution operator like crossover and variation, and each particle tracks the current optimal particle to realize the search for the solution space (Navalertporn and Afzulpurkar, 2011). Hence, we adopt the PSO algorithm to optimize the above-mentioned two parameters.

The performance of LS-SVM is defined as follows

$$\hbar = \frac{1}{M}\sum_{j=1}^{M}(y_i^j - \hat{y}_i^j)^2 \tag{9}$$

Actually, $\hbar$ can be viewed as the compound function of σ and γ. Therefore, we define the following optimization problem

$$\begin{aligned} \min_{\sigma,\gamma} \quad & \hbar = \frac{1}{M}\sum_{j=1}^{M}(y_i^j - \hat{y}_i^j)^2 \\ \text{s.t.} \quad & \gamma \in [\gamma_{\min}, \gamma_{\max}], \sigma \in [\sigma_{\min}, \sigma_{\max}] \end{aligned} \tag{10}$$

where $\sigma_{\min}$, $\sigma_{\max}$ and $\gamma_{\min}$, $\gamma_{\max}$ are the permitted minimum and maximum values.

In summary, we build the the LS-SVM model, at the same time, use the PSO algorithm to search the permitted area to decrease the fitness value $\hbar$ gradually. Finally, $\hbar$ converges to its minimum value, and corresponding σ and γ are the optimal algorithm parameters. Accordingly, corresponding α_j and b are the optimal model parameters of LS-SVM.

PSO based LS-SVM algorithm is given as follows,

Step 1. Load and preprocess the sample set.

Step 2. PSO initialization. Initialize algorithm parameters, initialize iteration counter $k = 0$, let the maximum iteration times $k_{\max}$ be a large positive integer, initialize maximum population size $\mathit{\Gamma}$, ω, and parameters c_1, c_2, r_1 and r_2 are random values in $[0, 1]$.
Initialize particles randomly and form the population. Generate initial velocities $\boldsymbol{V}_\tau = (v_{\tau 1}, v_{\tau 2})$ of each particle. Initialize particle's initial position $\boldsymbol{U}_\tau = (u_{\tau 1}, u_{\tau 2})$ as its best position $\boldsymbol{P}_{\text{p}}$, and the position with the best fitness $\hbar_\tau$ (calculated by Eq. (9)) of the all particles as the best position of the entire swarm $\boldsymbol{P}_{\text{g}}$.

Step 3. $k = k + 1$, update particles' position and velocity,

$$\begin{cases} \boldsymbol{V}_\tau = \omega \boldsymbol{V}_\tau + c_1 r_1(\boldsymbol{P}_{\text{p}} - \boldsymbol{U}_\tau) + c_2 r_2(\boldsymbol{P}_{\text{g}} - \boldsymbol{U}_\tau) \\ \boldsymbol{U}_\tau = \boldsymbol{U}_\tau + \boldsymbol{V}_\tau, \quad \tau = 1, \cdots, \mathit{\Gamma} \end{cases} \tag{11}$$

Step 4. Evaluate fitness $\hbar_\tau^{'}$ of new position and update the best position as follows. If $\hbar_\tau^{'} < \hbar_\tau$, then $\hbar_\tau = \hbar_\tau^{'}$ and the particle's best position $P_{\text{p}} = U_\tau$. Denote $\hbar_{\text{g}}^{'} = \min_{\tau=1}^{\mathit{\Gamma}} \hbar_\tau^{'}$, and corresponding position $P_{\text{g}}^{'}$ represents the new global best position. If $\hbar_{\text{g}}^{'} < \hbar_{\text{g}}$, then $\hbar_{\text{g}} = \hbar_{\text{g}}^{'}$ and $P_{\text{g}} = P_{\text{g}}^{'}$.

Step 5. If $k < k_{\max}$, turn back to step 3. Otherwise, the global best position P_{g} is the optimal parameter vector (γ, σ) of LS-SVM. With these optimal parameters, the LS-SVM optimal model can be calculated by Eq. (7).

By applying above PSO based LS-SVM algorithm, three data-based models in regarding with grade, yields and GPD can be established respectively. In this sense, the MOP as shown in Eq. (3) is completely formulated. In the following, this MOP will be solved based on MOEAs.

3.2 NSGA-II based optimization strategy for the GGBS production process

Since EAs have great advantages in solving MOPs, in recent years, many MOEAs have emerged and show satisfying performance. Adopting the elite decision and diversity preservation mechanisms, NSGA-II shows excellent characters such as good performance, high efficiency and simple computation, and is one of the most successful and commonly used MOEAs.

The main procedure of NSGA-II algorithm is shown in Algorithm 1.

4 Simulation

In this section, the PSO based LS-SVM model of the GGBS production process is established based on process data. Thereafter, the NSGA-II method is applied on this model to obtain the optimal solution of the multiobjective problem.

4.1 Data-based model validation

Firstly, the PSO based LS-SVM model of the GGB-S production process is established based on the PSO based LS-SVM algorithm. According to the operation

Algorithm 1 NSGA-II algorithm

begin:

Initialize the parent population P_0 randomly;

Based on nondomination, P_0 is sorted, and according to nondomination level, each solution is assigned a fitness value;

After selection, recombination and mutation, offspring population Q_0 of size N is created.

while Generation times less than the maximum **do**

New population R_t of size $2N$ is generated by combining members of previous population P_t and current population Q_t, i.e. $R_t = P_t \bigcup Q_t$.

Sort R_t based on constrained nondomination, and a series of non-dominated set F_i and corresponding fitness are generated.

New population P_{t+1} of size N is generated from F_i based on the following principles,

1. Select F_i if $i < j$.

2. Select the member in F_i with less crowding distance in the ith level.

Create a new offspring population Q_{t+1} of size N after selection, crossover and mutation.

$t = t + 1$.

end while

report of LUXIN GGBS mill line 3, we selected 200 samples from the preprocessed data as the training sample set $S_{\text{tr}} = \{\boldsymbol{x}^j, \boldsymbol{y}^j\}_{j=1}^{200}$ and 100 samples as the test sample set $S_{\text{te}} = \{\boldsymbol{x}^j, \boldsymbol{y}^j\}_{j=1}^{100}$, where $\boldsymbol{x}^j \in R^6$ is the input vector and $y_i^j \in R$, $i = 1, 2, 3$ are the outputs for SSA, yields and GPD respectively. To optimize the LS-SVM parameters γ and σ, a PSO algorithm is introduced with parameters set up as $\Gamma = 20$, $\omega = 0.6$, $k_{\max} = 200$, $c_1 = 0.5$, $c_2 = 0.7$, $\gamma \in [0.01, 1000]$, $\sigma \in [0.1, 100]$. As a result, three models in regarding with SSA, yields and GPD are obtained respectively as in Fig. 6–8. Optimal parameters (σ, γ), cross validation mean square error (CV MSE), training and test errors of those three models are shown in Table 4.

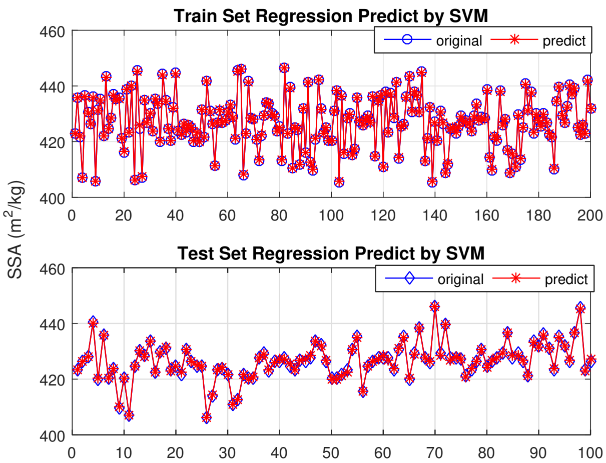

Fig. 6 PSO based LS-SVM model of SSA

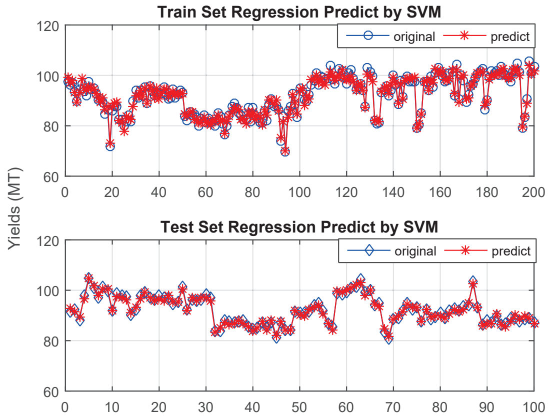

Fig. 7 PSO based LS-SVM model of GGBS yields

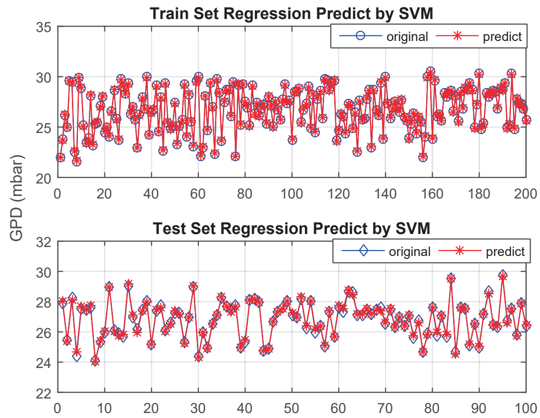

Fig. 8 PSO based LS-SVM model of GPD

Table 4 Optimal parameters and modeling error

Model	(σ, γ)	CV MSE	Train MSE	Test MSE
SSA	$(15.5599, 62.1863)$	0.047428	0.1683	0.2312
Yields	$(0.0172, 67.2530)$	0.001596	0.0074	0.0088
GPD	$(0.0016, 51.7413)$	0.017194	1.8317	0.7082

As seen in Fig. 6–8 and Table 4, for the three data-based models, the training and testing errors are very small, which means the estimated value can fit and predict the actual value precisely. Due to the severely fluctuated material components in mill and many unpredictable conditions, above data-based models show satisfying performance and can be used to provide the basis for optimal control of vertical mill.

4.2 Optimal solutions by MOEA algorithms

For the MO problem of GGBS production process formulated as (3), based on the three LS-SVM model,

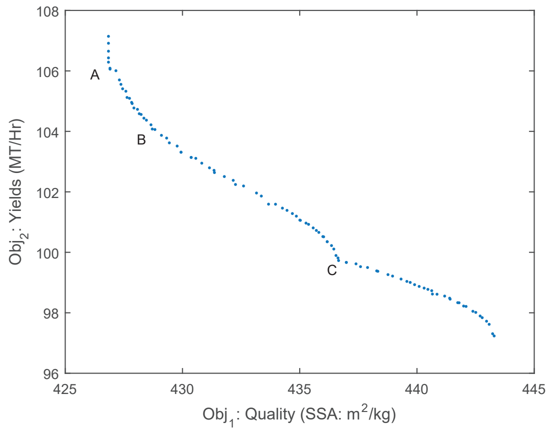

Fig. 9 Optimal solutions by NSGA-II algorithm

NSGA-II algorithm is applied to search the optimal solutions. Fig. 9 gives the Pareto-optimal front for the quality and yields of GGBS production process. The quality of SSA decreases with the increasing of SSA yields. This kind of negative correlation is in accordance with the mechanism and data analysis in section 2.4. Considering customer's needs in terms of quality, relevant technical staff can choose appropriate operating conditions from the Pareto-optimal solutions to improve the yields of product and maximize the comprehensive benefit. It can be observed that a minimum of quality is incurred no matter what the yields is beyond point A. This case matches the fact that in production process, when the yields is more than 106 MT per hour, the SSA of GGBS product will not be improved although the yields is decreased.

Further more, it should be noted that point B and point C are the two most interesting solutions for decision maker, which are called the 'knees' by Branke et al (2004). These two solutions are characterized that around these points, a small improvement in either direction will cause a large deterioration in the other direction. This character makes moving towards any objective not attractive for decision maker.

Table 5 Statical information about HV value of different MOEAs

Method	Mean	Standard deviation
NSGA-II	224.9827	10.94632
NSGA-II+SBS	227.8992	10.61037
NSGA-III	226.0506	12.79157

According to historical data and the expertise from domain experts, obtained Pareto-optimal solutions by NSGA-II algorithm as shown in Fig. 9 can be an effective guidance to optimize the GGBS production process. To better verify the performance of the NSGA-II algorithm in dealing with the MOP of the GGBS production process, we take some state-of-the-art MOEAs like NSGA-III (Jain and Deb, 2014) and NSGA-II+SBS (Li et al, 2014) as comparison. The performance metric is defined by Hypervolume (HV) which gives a comprehensive evaluation, including the convergence, diversity and uniformity of the obtained solutions (Hierons et al, 2016). By running above two algorithms and NSGA-II for 30 independent runs respectively for the GGBS production process, the statical information including mean and standard deviation of above three kind of methods are shown in Table 5. Table 6 shows that there is no significant difference among the performances of three algorithms at a 0.05 level of significance by a two-tailed *t*-test. In this case, the relative simple and easy-to-use NSGA-II algorithm has satisfying performance on the convergence, diversity and uniformity of the obtained solutions and it is selected to solve the GGBS MO problem.

Table 6 Significance of different methods

	NSGA-II	NSGA-II+SBS	NSGA-III
NSGA-II	1	0.299	0.730
NSGA-II+SBS	0.299	1	0.545
NSGA-III	0.730	0.545	1

5 Conclusion

The GGBS production process is analyzed to be an MOP. Based on the intrinsic characteristic that the process is hard to be mathematically modeled, data-based models between objectives and variables are established using the PSO based LS-SVM method. Further, several constrained MOEAs are introduced to obtain the Pareto-optimal solutions for the best yields and quality of GGBS production, at the same time, the modeled grinding pressure difference is guaranteed to vary in given range to maintain the production process stable. Experiment shows that the established models are effective and the obtained Pareto-optimal solutions supply important guidance to optimize the production process.

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Compliance with ethical standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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